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Automated prediction of cardiorespiratory deterioration in patients with single ventricle parallel circulation: A multi-center validation study

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The Institutional Review Board (IRB) or equivalent ethics committee of the Authors’ Institutions approved the study protocol and publication of data (IRB# H-33066, approval date 7/3/2013). The patient(s) provided informed written consent for the publication of the study data.
Central Message: 53.6% of all cardiorespiratory deterioration events can be predicted in children with single ventricle physiology during their hospitalization after stage 1 palliation.

Perspective Statement: Patients with single ventricle physiology have a significant risk of cardiorespiratory deterioration between their first and second stage palliation surgeries. Detection of deterioration episodes may allow for early intervention and improved outcomes. We have developed an automated algorithm to predict such events 1-2 hours before they happen.

Abbreviated legend for your Central Picture: Performance of our algorithm for prediction cardiorespiratory deterioration.
ABSTRACT

Objectives: Patients with single ventricle physiology have a significant risk of cardiorespiratory deterioration between their first and second stage palliation surgeries. Detection of deterioration episodes may allow for early intervention and improved outcomes.

Methods: A prospective study was executed at Nationwide Children’s Hospital, Children’s Hospital of Philadelphia, and Children’s Hospital Colorado to collect physiologic data of subjects with single ventricle physiology during all hospitalizations between neonatal palliation and II surgeries using the Sickbay software platform (Medical Informatics Corp, Houston, TX). Timing of cardiorespiratory deterioration events was captured via chart review. The predictive algorithm previously developed and validated at Texas Children’s Hospital was applied to this data without retraining. Standard metrics such as ROC area, positive and negative likelihood ratio, and alert rates were calculated to establish clinical performance of the predictive algorithm.

Results: Our cohort consisted of 58 subjects admitted to the cardiac ICU and stepdown units of participating centers over 14 months. Approximately 28,991 hours of high-resolution physiologic waveform and vital sign data was collected using the Sickbay. A total of 30 cardiorespiratory deterioration events were observed. The Risk Index metric generated by our algorithm was found to be both sensitive and specific for detecting impending events one to two hours in advance of overt extremis (ROC = 0.927).

Conclusions: Our algorithm can provide a 1-2 hour advanced warning for 53.6% of all cardiorespiratory deterioration events in children with single ventricle physiology during their initial postop course as well as interstage hospitalizations after stage 1 palliation with only 2.5 alarms being generated per patient per day.
Patients with single ventricle physiology have a significant risk of cardiorespiratory deterioration between their first and second stage palliation surgeries. The objective of this study was to validate a real-time computer algorithm which can automatically recognize physiologic precursors of cardiorespiratory deterioration in children with single ventricle physiology during their initial postop course as well as interstage hospitalizations after stage 1 palliation across multiple tertiary hospitals in the USA. A logistic regression model was trained to separate the physiologic dynamics of a pre-deterioration phase from all other data generated by 58 study subjects. Our algorithm demonstrated a 1-2 hour advanced warning for 53.6% of all cardiorespiratory deterioration events in children with single ventricle physiology, with only 2.5 alarms being generated per patient per day.

KEY WORDS: clinical deterioration; prediction algorithm; single ventricle physiology; arrest prediction; data mining; forecasting

ABBREVIATIONS:
RVPAS: Right ventricle to pulmonary artery shunt
BTS: Blalock-Taussig shunt
PA: Pulmonary artery
PDA: Patent Ductus Arteriosus
BAS: Balloon atrial septostomy
NCH: Nationwide Children’s Hospital
CHOP: Children’s Hospital of Philadelphia
CHCO: Children’s Hospital Colorado
BCM – Baylor College of Medicine
CICU – Cardiovascular Intensive Care Unit
HR: Heart rate
HRV: Heart rate variability
SpO2: Peripheral arterial oxygen saturation
ST: ST-segment elevation
STV: ST-segment variability
PVC: Frequency of premature ventricular contractions
PVI: Pleth variability index
ECG - Electrocardiogram
ROC – Receiver Operating Curve
RI – Risk Index
TPR - true positive rate
FPR - false positive rate
PLR: Positive likelihood ratio
NLR: Negative likelihood ratio
MCC - Matthews correlation coefficient
**Introduction**

Patients with single ventricle lesions account for 2-3% of all congenital heart disease (1) but are responsible for up to 25-40% of all neonatal cardiac deaths (2–4). The time period of highest risk for these patients is in the immediate post-operative period after neonatal palliation (5,6). During this time period, patients have a parallel circulatory system in which a single functioning ventricle perfuses both the systemic and pulmonary circuits. Such a circuit is inherently unstable as changes in pulmonary or systemic vascular resistances can affect systemic oxygen delivery significantly, resulting sudden and unexpected patient deterioration. As a result, mortality between neonatal palliation and stage II surgeries for this population is approximately 15% and studies suggest that cardiorespiratory arrests account for 63% of the identifiable causes of death during this time period (7).

We have previously developed and tested an automated algorithm which can predict impending clinical deterioration events in this population, during their hospitalization, 1-2 hours in advance of overt symptoms with high sensitivity and specificity in a large single-center study (8,9). In this report, we present the results of a multi-center validation study designed to measure the performance of the same algorithm when exposed to different clinical practice patterns at several tertiary pediatric heart centers in the US. To our knowledge, this is the first fully automated algorithm for predicting *acute* cardiorespiratory deterioration events not only continuously and in real-time, but also validated in an independent, multi-center study. While generalized risk models have been developed, none currently provide a warning of the immediate risk of an acute event (10–12).
Methods

Subjects, deterioration events, and data collection

The study was designed as a prospective, observational, multi-center validation study. Study subjects were recruited, consented, and prospectively enrolled at three leading pediatric heart centers in the United States between 5-9-2018 and 9-24-2019. Participating centers included Nationwide Children’s Hospital, Children’s Hospital of Philadelphia, and Children’s Hospital Colorado. The Institutional Review Board (IRB) or equivalent ethics committee of the Authors’ Institutions approved the study protocol and publication of data (IRB# H-33066, approval date 7/3/2013). The patient(s) provided informed written consent for the publication of the study data. The inclusion criteria for the study were infants born with morphologic hypoplasia of either the right or left ventricles of the heart and underwent neonatal palliation surgery to establish parallel circulation. Study subjects were admitted to the cardiovascular intensive care units (CICU) at their respective centers immediately after their neonatal surgical palliation. Study enrollment terminated either at the time of stage II palliation surgery, patient discharge home, patient withdrawal, or expiration.

The physiological data from all study subjects were recorded from their post-op Norwood hospitalization and any hospitalization during inter-stage period in both the ICU and step-down units. If a subject was discharged and later re-admitted, the physiologic data from this re-admission was included in the study (i.e. the patient had not received stage 2 palliation). Physiologic data were acquired continuously using the FDA cleared, Sickbay™ patient monitoring and analytics platform (510k - K143304, Medical Informatics Corporation, Houston, Texas). Physiologic signals included high-resolution waveforms
(ECG, photoplethysmogram) and low-resolution vital signs calculated by the bedside monitors (heart rate, arterial oxygen saturation, ST segment elevations, premature ventricular contractions). The Sickbay platform collected, processed, stored, and de-identified the data as well as executed data analysis using its research APIs and development environment.

Cardiorespiratory deterioration events were defined as either a cardiac arrest requiring cardiopulmonary resuscitation, ECMO, or an unplanned intubation. The approximate time of each deterioration event was first obtained via chart review and confirmed to the exact minute by clinical investigators using the physiological recordings of heart and respiratory rates. The physiological data generated by the cohort was labeled as either pre-deterioration data or non-deterioration data. The pre-deterioration data included signals recorded between 1 to 2 hours before the event. The non-deterioration data included all physiologic signals recorded more than 2 hours before or more than 48 hours after a deterioration event. Data labels were used to assess the performance of the algorithm.

**Data processing**

The classification algorithm developed in (8) uses 7 input variables calculated from the physiologic signals. The 7 input metrics include: heart rate (HR), heart rate variability (HRV), peripheral arterial oxygen saturation (SpO2), ST-segment elevation (ST), ST-segment variability (STV), frequency of premature ventricular contractions (PVC), and the pleth variability index (PVI). The HR, SpO2, ST and PVC were acquired directly from the standard bedside monitor by averaging the raw signals over 5-minute windows. The HRV, STV and PVI require additional processing steps. The HRV was processed from the ECG waveform by calculating the time lapsed between R-peaks to obtain the instantaneous
frequency of cardiac beats. The HRV was then defined as the standard deviation of the beat-to-beat frequencies collected over a window of 5 minutes. The STV, defined in detail in (13), quantifies the change of the ST-segment vector every 30 seconds using 3-dimensional orthogonal projections estimated from the ST-segment elevations from the V₅, aVL, and II ECG leads. The magnitude of the 30-second changes is averaged over 5-minute windows. The PVI is an estimate of the amplitude modulation of the plethysmograph waveform at a frequency band around the respiration rate. As a surrogate for the pulse pressure variability, the PVI is associated with volume responsiveness (14). Using this approach, PVI was computed every minute and then averaged over 5-minute windows.

The classification algorithms developed in (8) is based on a logistic regression to compute a risk index of the form

\[ RI = \exp \sum_{j=1}^{7} \beta_j \frac{x_j - \mu_j}{\sigma_j} \]

where \( RI \) is the risk index associated with the input variables \((x_1, x_2, \ldots, x_7)\) in the pre-deterioration dataset, and \( \mu_j \) and \( \sigma_j \) are used to normalize the variables. Each of the input variables \( x_j \) at a given time \( t \) were computed as deviation of the physiologic metrics from their moving baselines values as follows

\[ x_j(t) = y_j(t) - y_j^{base}(t) \]

where \( y_1 = \text{HR}, y_2 = \text{HRV}, y_3 = \text{SpO}_2, y_4 = \text{ST}, y_5 = \text{STV}, y_6 = \text{PVC}, \) and \( y_7 = \text{PVI}, \) and \( y_j^{base}(t) \) is the moving baseline value of the metric \( j \) calculated as the average of \( y_j \) over a window of time that starts 24 hours before time \( t \) and ends 12 hours before time \( t \). The
same coefficients from (8) were used to validate this classification model with the independent data from study sites.

**Algorithm performance**

Once the logistic input variables ($x_1, x_2, \ldots, x_7$) were computed, the risk index $RI$ was calculated according to equation (1) for every 5-minute interval for each subject in the cohort. The performance of this classification was quantified using the area under the receiver operating characteristic (ROC) curve as a threshold-independent metric. For thresholds ranging from 0.1 to 100 to classify $RI$ as either pre-deterioration or non-deterioration, we also computed the true positive rate (TPR), false positive rate (FPR), Matthews correlation coefficient (MCC), positive likelihood ratio (PLR) and negative likelihood ratio (NLR).

**Results**

The study cohort included 58 (CHOP (N=27), CHCO (N=10), NCH (N=21)) subjects who produced usable data for the validation analysis. Study subjects experienced 30 deterioration events over the course of their hospitalization between neonatal palliation and stage II surgeries, while physiologic data was being recorded, 12 of which were found to be cardiac arrests and 18 were respiratory events. Two subjects withdrew from the study, neither of which experienced a deterioration event. A review of discharge dates after the neonatal palliations revealed that 60% of the events (18 out of 30) occurred before the discharge date of the first hospitalization. The rest of the events occurred during re-hospitalizations but prior to the stage II palliation. Twenty-one subjects
experienced at least one event. Ten patients expired during the study yielding a mortality of 17.2%. Figure 1 displays a histogram of deterioration events relative to neonatal palliation date. It was observed that 50% of the deterioration events occurred within the first 30 days after neonatal palliation. Table 1 describes the types of neonatal palliative procedures for the cohort and the prevalence of deterioration events. The Norwood procedure was found to be the most prevalent surgery, and accounted for 66% of the neonatal palliations in the cohort.

Between neonatal palliation and stage II palliations was a median of 141 days [IQR=126-155]. For the entire cohort, the cumulative time in between neonatal palliation and stage II palliations was 206,088 hours. The cumulative time between admission and discharge dates of the first hospitalization was 59,760 hours. There were 28,991 hours with recorded physiological data.

The classification algorithm developed in (8) was evaluated on the 7 physiologic metrics from the multi-site validation cohort. Since this data was labeled as either non-deterioration or pre-deterioration according to its proximity to deterioration events, the performance of the classification algorithm was assessed.

Model performance metrics are illustrated in Figure 2. The area under the receiving operating characteristic curve was found to be 0.927. The positive likelihood ratio was found to be between 30 and 80 for risk index thresholds between 1-10. This indicates that should the algorithm alert at the specified threshold, the patient is 30-80x more likely to
experience a deterioration event in the next 1-2 hours compared to the time when the algorithm does not alert.

Automated alerts of impending deterioration can be generated by assigning a threshold value to the RI. Table 2 displays the relationship between the number of alerts generated by the algorithm and the corresponding true positive rates for cardiorespiratory deterioration events as a function of a specific alert threshold. Results indicate that 46-53% of all cardiorespiratory deterioration events can be predicted 1-2 hours in advance by the algorithm. Results indicate that cardiac events are more accurately predicted compared to respiratory events.

Table 3 illustrates the performance of the predictive model separated by study site. While the results suggest that there is a slight increase in predictive performance in site 1 compared to the others, the model still was found to have still have significant performance, indicating that the model is generalizing well across different sites consistently.

Discussion

Computer algorithms will never replace trained medical personnel. However, they can be used to augment and enhance the capabilities of the clinician, and make the medical care environment safer for patients and more efficient for providers. This is part of an ongoing shift in critical care management referred to as virtual critical care, the idea that several layers of clinical assets (local providers, remote providers, and algorithmic surveillance) can coordinate together virtually to form a unified system of patient oversight. Algorithmic surveillance plays a key role in virtual care systems as it provides a scalable means of
identifying key moments in time when human intervention is most needed and resources can be efficiently deployed (15).

The ability to detect sudden acute deterioration events immediately before they occur allows the care team to take time-critical corrective actions to prevent these sub-clinical events from progressing to life-threatening ones. As a result, this work represents a shift in the way these patients are monitored in hospital: moving away from standard physiologic data acquisition at the bedside and instead focusing on automating physiologic data interpretation. In this way, automated monitoring can provide a scalable layer of advanced algorithmic surveillance for patients. While no algorithm will ever replace a physician or nurse, algorithms working in real-time with the care team can make patient surveillance more efficient and effective than either can achieve on their own.

Our study demonstrated that the majority of cardiorespiratory deterioration events which occurred during the hospitalization of single ventricle population prior to stage 2 palliation can be predicted 1-2 hours in advance of overt symptoms using automated, algorithmic surveillance. With an update frequency of 5 minutes, the algorithm can detect subtle, moment-to-moment physiologic changes that may occur throughout the hospitalization, such as a bath. Furthermore, our study demonstrated that the physiologic signs of pre-deterioration in this population are not specific to a particular clinical environments or practice patterns. The algorithm appears to be translatable across institutions and clinical environments as both ICU and step-down units were included in the analysis. Cardiac events seem to be more consistently predictable than respiratory deteriorations. This is likely the case as cardiac events are often more discrete and unambiguous compared to respiratory events, which may have more clinical subjectivity around their recognition.
The natural imprecision in the recognition of respiratory events leads to lower predictive performance.

There is, however, a tradeoff between predictive performance and the number of alerts that are generated in the care environment. The higher the alerting threshold, the lower the number of alerts generated, but the lower the TPR. The selection of the alerting threshold allows an institution to balance the predictive performance of the algorithm with the load that the algorithm will place on the care team. For example, at an alert threshold of 1, the median number of alerts generated by the algorithm is 2.5 alerts per patient per day, but the TPR is 54%. What this means is that if the care team responded to these 2.5 alerts per patient per day, they would be able to anticipate 54% of all deterioration events 1-2 hours before they happen. In context, there are typically 100-400 alarms per patient per day in this population generated from existing bedside devices.

Such an algorithm may have utility even when it fails to forecast an event. Fundamentally, this algorithm has been trained to recognize the physiological fingerprint associated with the sub-clinical precursors of a critical deterioration event. If a patient experiences an event, and no such clinical precursors are present (as would be indicated by a low value of the risk index), then this may suggest a different etiology, such as shunt thrombosis.

There are several limitations to this study. First, the predictive algorithm does not explicitly consider the types of cardiac lesion, post-surgical anatomy, laboratory values, comorbidities, and other health characteristics. Although all the patients included in the study have parallel circulation, there are differences in physiology between anatomies that may influence the patient’s susceptibility to cardiopulmonary deteriorations and
response to interventions (16–18). The incorporation of these categorical features into a predictive algorithm may require a much larger sample size not presently available, and the algorithm was found to generalize well across centers and types of cardiac lesions. Second, pulmonary deterioration and the precise time for intubation may be ambiguous as they depend to some extent on clinical judgement. Therefore, any algorithm attempting to predict these events with high precision may have difficulties. Finally, while the algorithm may be able to predict deterioration events in the near future accurately, the clinical benefit of this prediction has yet to be determined. Measuring the potential outcomes benefit related to this algorithm paired with an intervention protocol is planned as a future multi-center clinical trial.

**Conclusion**

We have demonstrated that there exist subtle, yet detectable, physiologic changes in the hours preceding cardiorespiratory deterioration in children with single ventricle physiology. We have validated an algorithm that was trained to detect these changes in this population. A multi-center trial showed that this algorithm was able to predict 53.6% of all cardiorespiratory deterioration 1-2 hours before they happened with only 2.5 alarms being generated per patient per day.
References


Figure Captions

**Figure 1:** Observed timing of deterioration events relative to neonatal palliation date.

**Figure 2.** Performance characteristics. Top-left: Receiver-operating characteristic curve. Top-right: True positive rate (TPR) and false positive rate (FPR) as functions of the risk index (RI) threshold. Bottom-left: Matthews correlation coefficient (MCC) as a function of the RI threshold. Bottom-right: Positive likelihood ratio (PLR) and negative likelihood ratio (NLR) as a function of the RI threshold.
<table>
<thead>
<tr>
<th>Palliation type</th>
<th>Patients, n (%)</th>
<th>Events, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norwood (all)</td>
<td>38 (66%)</td>
<td>17 (57%)</td>
</tr>
<tr>
<td>Norwood with RVPAS</td>
<td>23 (40%)</td>
<td>12 (40%)</td>
</tr>
<tr>
<td>Norwood with BTS</td>
<td>4 (7%)</td>
<td>2 (7%)</td>
</tr>
<tr>
<td>Norwood with Sano</td>
<td>11 (19%)</td>
<td>3 (10%)</td>
</tr>
<tr>
<td>Hybrid</td>
<td>4 (7%)</td>
<td>1 (3%)</td>
</tr>
<tr>
<td>Aortic arch repair + PA band</td>
<td>4 (7%)</td>
<td>5 (17%)</td>
</tr>
<tr>
<td>Blalock-Taussig shunt</td>
<td>2 (3%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Central shunt</td>
<td>2 (3%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>PA band</td>
<td>3 (5%)</td>
<td>2 (7%)</td>
</tr>
<tr>
<td>PDA stent + BAS</td>
<td>3 (5%)</td>
<td>5 (17%)</td>
</tr>
<tr>
<td>Withdrawn</td>
<td>2 (3%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td><strong>58 (100%)</strong></td>
<td><strong>30 (100%)</strong></td>
</tr>
</tbody>
</table>

**Table 1:** Breakdown of the cohort by type of surgical palliation.
<table>
<thead>
<tr>
<th>Risk Index Threshold</th>
<th>Matthews Correlation Coefficient</th>
<th>TPR Overall, Cardiac Events, Respiratory Events, Alarms per Day per Patient, median (iqr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.27</td>
<td>53.61 67.86 31.48 2.07 2.5 (1.5-5.4)</td>
</tr>
<tr>
<td>1.5</td>
<td>0.30</td>
<td>46.37 56.40 17.23 1.27 1.3 (0.1-3.8)</td>
</tr>
<tr>
<td>2</td>
<td>0.29</td>
<td>39.14 48.54 11.08 0.89 1.1 (0.0-2.4)</td>
</tr>
<tr>
<td>3</td>
<td>0.32</td>
<td>34.78 45.34 7.41 0.56 0.4 (0.0-1.4)</td>
</tr>
<tr>
<td>4</td>
<td>0.33</td>
<td>31.94 39.89 7.41 0.42 0.2 (0.0-1.0)</td>
</tr>
<tr>
<td>5</td>
<td>0.34</td>
<td>30.25 35.75 7.41 0.33 0.0 (0.0-0.6)</td>
</tr>
<tr>
<td>6</td>
<td>0.31</td>
<td>26.01 32.47 5.56 0.28 0.0 (0.0-0.5)</td>
</tr>
</tbody>
</table>

Table 2. Performance characteristics for the evaluation of the predictive model.
Table 3: Performance characteristics for the evaluation of the predictive model broken down by study site.

<table>
<thead>
<tr>
<th>Risk Index Threshold</th>
<th>Site 1</th>
<th></th>
<th>Site 2</th>
<th></th>
<th>Site 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TPR, %</td>
<td>FPR, %</td>
<td>TPR, %</td>
<td>FPR, %</td>
<td>TPR, %</td>
</tr>
<tr>
<td>1</td>
<td>65.6</td>
<td>3.4</td>
<td>51.5</td>
<td>1.6</td>
<td>50.8</td>
</tr>
<tr>
<td>1.5</td>
<td>65.6</td>
<td>2.3</td>
<td>39.1</td>
<td>0.9</td>
<td>44.3</td>
</tr>
<tr>
<td>2</td>
<td>62.4</td>
<td>1.8</td>
<td>32.6</td>
<td>0.7</td>
<td>39.3</td>
</tr>
<tr>
<td>3</td>
<td>56.3</td>
<td>1.2</td>
<td>23.8</td>
<td>0.4</td>
<td>34.4</td>
</tr>
</tbody>
</table>